Source Smartphone Identification Using Sensor Pattern Noise and Wavelet Transform

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Abstract

The ability to identify the source camera for an image has application in the areas of digital forensics and multimedia data mining. The majority of previous research in this area has focused on primary function imaging devices (i.e. digital cameras). In this work we use the pattern noise of an imaging sensor to classify digital photographs according to the source smartphone from which they originated. This is timely work as new smartphone models large imaging sensors, affording significant improvements in classification rates using pattern noise. Our approach is to extract wavelet based features which are then classified using a support vector machine. We show that this method generalises well when the number of source cameras is increased.

1 Introduction

Often the pictures are considered a piece of truth as being real events captured by electronic devices (cameras). However, with the development of technology have emerged powerful and sophisticated tools that facilitate in an impressive manner the alteration of digital images, even for those without technical knowledge or expertise in the area [11].

Due increasing storage capacity, usability, portability and affordability, camera enabled mobile phones have become ubiquitous consumer electronic devices. The extensive use of smartphone cameras makes enforcing legal restrictions on the capture and sharing of digital photographs very difficult. Restrictions on the use of cameras include locations such as schools, government offices and businesses. Consequently, tools which permit the identification of source devices have significant utility various areas of law enforcement [2] such as child protection and digital rights management.

2 Source Camera Identification Techniques

Research in this field typically determines make and model by identifying characteristic artefacts within an image. The success of these techniques depend on the assumption that all the images acquired by the same device have intrinsic characteristics of the device [22]. The main problem with this approach is that different models of digital camera are often built using the same core components that originate from a small number of manufacturers. As a consequence it is difficult or impossible to differentiate between models using such methods.

During the image generation process the lens system can introduce some aberrations. In [8] the lens radial distortion is proposed as the best technique for source identification. Radial distortion causes straight lines appear as curves in images. The degree of radial distortion for each image can be measured by a process consisting of three steps: edge detection, distorted segment extraction, and distortion error measurement. They experimented with three different cameras and obtained 91.28% source camera identification accuracy.

In [3] an algorithm for identifying and classifying color interpolation operations is presented. This method is based on two methods to perform the classification process: first using an algorithm to analyse the correlation of each pixel value with values of its neighbouring pixels, and secondly an analysis of the differences between pixels independently. The source camera identification results with images from four to five different models resulted an accuracy of 88% and 84.8% respectively.

Between pixel correlations for source identification were also used in [15], obtaining a coefficient matrix for each color channel while defining a pixel quadratic correlation model. A neural network classifier was used, achieving a success rate of 98.6%. This approach is not efficient for differentiating between different models from the same manufacturer.

In [4] a set of binary similarity measures is used as metrics to estimate the similarity between image bit planes. The fundamental assumption of this work is that *Color Filter Array*

(CFA) interpolation algorithms from each make leaves correlations along image bit planes and can be represented by a set of 108 binary similarity measures for classification. The success rate of their experiment was between 81% and 98% when attempting to classify three cameras which decreased to 62% when nine cameras were considered.

In [18] the authors extend the source identification to different devices such as mobiles phones, digital cameras and scanners. Color interpolation coefficients and noise characteristics are used to classify. Their experimentsshowed an overall result of 93.75% accuracy. When identifying the make and model of five mobile phone models, a 97.7% accuracy was obtained.

In [19] a method based on bi-coherence statistics phases and magnitudes along with the wavelet coefficients is used. This method captures the unique nonlinear distortions in the wavelet domain produced by the cameras when performing processing operations over images. As a result an accuracy of 97% in the identification was obtained in distinguishing different models from the same manufacturer.

In [23] a method for identifying the source camera through wavelet features statistics is presented. The standout wavelet domain features are extracted to integrate a statistical model of image including 216 first-order wavelet features and 135 co-occurrence second order characteristics. In this study wavelet domain characteristics are considered the most representative and are preferred over the spatial characteristics (color of the image and *Image Quality Metrics* (IQM)) and CFA. Under the same conditions as in the experiments performed in [19] fail to distinguish between different models of the same maker, the average accuracy rate was 98%.

A technique to differentiate images using the wavelet family transforms is explained in [20] . Ridgelets and contourlets subband statistical models are proposed to extract the representative features from images. Experiments were conducted to identify three different cameras obtaining accuracies of: 93.3% with wavelet-based approach, 96.7% using ridgelets, and 99.7% with contourlets.

In [14] a method using the marginal density of *Discrete Cosine Transform* (DCT) coefficients in low-frequency coordinates and neighbouring joint density features on both intra-block and inter-block from the DCT domain is proposed. In experiments with images of different scale factors from five smartphone models of four manufacturers, an accuracy between 86.36% and 99.91% was obtained.

The techniques based on sensor noise are rely on studying the traces left by sensor defects in images. There are broadly two different approaches: pixel defects and sensor pattern noise *Sensor Pattern Noise* (SPN). Pixel defects include hot pixels, dead pixels, the row or column defects and group defects. The SPN method estimates a device 'fingerprint' by averaging multiple residual noise images computed by the application of a denoising filter. The presence of the pattern is determined using a correlation method or machine classification *Support Vector Machine* (SVM).

In [10], pixel defects of *Charge Coupled Device* (CCD) sensors are studied, focusing on different image features and identify their source. The source considered were CCD sensor defects, the file format, image noise and watermarking introduced by manufacturer. CCD sensor defects included hot spots, dead pixels, group defects, and row/column defects. Results indicated that each camera has a different defect pattern. Nevertheless, it is also noted that the number of pixel defects for images from the same camera is different and varies greatly depending in the image content. Similarly, it was shown that the number of defects varies with temperature. The study concluded that high quality CCD cameras produce images with fewer defects than other sensor types. When considering only defective CCD sensors, this study is not applicable to the analysis of images generated by mobile devices.

In [16] the authors use SPN to create fingerprints which were used to uniquely identify cameras of different make and model. To identify the camera from a given image, the reference pattern is considered as a watermark in the image and its presence is established by a correlation detector. It was found that this method is affected by processing algorithms such as image JPEG compression and gamma correction. The results for pictures with different sizes were unsatisfactory [22].

In [9] an approach to source camera identification using an 'open set' scenario is proposed for which, unlike previous work, the access to the source camera is not required to perform the analysis. This approach, in contrast to others, considers 9 different *Region Of Interest*s (ROIs) located in the corners and the center of the images (not only the central region of the image). Using these ROIs it is possible to work with different resolution images without requiring zero padding or color interpolation. The SPN is computed for each color channel generating a total of 36 representative features for each image. Then, the image features are labelled as positive class (created from particular camera) or negative class (originating from another camera). After the SVM training phase, the separating hyperplane is moved by a given amount either inward (for positive classes) or out (for negative classes) for to accommodate the open set scenario. The results of their experiments had an accuracy of 94.49%, 96.77% and 98.10%.

The basic SPN method described in [16] is developed further by [12]. They propose that the stronger is a component of the sensor noise is less reliable and therefore it should be attenuated. They performed experiments with six different cameras.For images of 1536×2048 pixels, they obtained an accuracy of 38.5 % with the implementation without the improvement and 80.8% with the proposed improvement. For images of 512×512 pixels they obtained an accuracy of 21.8% without improvement and 78.7% with the proposed improvement.

A detailed comparison of different source identification techniques is presented in [21].

3 Source Identification Algorithm

Previous work has shown sensor pattern noise [10] [12] [16] and wavelet transform [19] [20] to be an effective method for source camera identification. However, almost all studies have focused only traditional cameras excluding mobile cameras. This makes it an area of study that requires attention. Using a biometric analogy, we consider each noise pattern to be a fingerprint of its source camera's sensor.

In our study, sensor pattern noise is used to classify images captured by, camera enabled, smartphones. Our approach characterises the fingerprints using wavelet based feature vectors. The scheme presented in Figure 1 shows the functional diagram of our proposal.

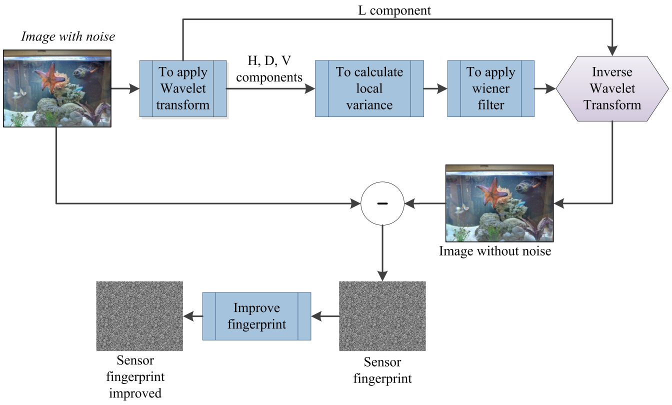

Figure 1. Scheme functional.

Noise images were obtained using the method previously described by [16] also summarised by Algorithm 1 as follows.

Algorithm 1: Extracting PRNU

Input: Image I

Variance estimation: adaptive or non-adaptive

Result: Sensor fingerprint I_{noise}

procedure EXTRACTPRNU(I)

Apply a wavelet decomposition in 4 levels to I;

foreach *wavelet decomposition level* **do**

foreach *component* $c \in \{H, V, D\}$ **do**

Compute the local variance;

if *adaptive variance* **then**

Compute 4 variances with windows of size: 3, 5, 7 and 9 respectively;

Select the minimum variance;

else

Compute the variance with a window of size 3;

Compute noiseless wavelet components applying the Wiener filter to the variance;

Obtain I_{clean} by applying the inverse wavelet transform with clean components calculated;

Obtain the sensor noise with $I_{noise}=I-I_{clean}$;

Apply zero-meaning to I_{noise};

Increase the green channel weight with $I_{noise}= 0.3\cdot I_{noise_R}+0.6\cdot I_{noise_G}+0.1\cdot I_{noise_B}$;

end procedure

To extract its noise pattern, an image is decomposed into its color channels (R, G, B). Then, a four-level wavelet decomposition of each color channel is calculated using the Daubechies, 8-tap, *Separable Quadrate Mirror Filters* (QMF). The number of decomposition levels can be increased to improve accuracy or reduced to reduce processing time.

Horizonal H, vertical V and diagonal D high-frequency images are obtained for each level of decomposition. For each detail image, the local scene variance in a $W \times W$ window is estimated. Four estimates are obtained with window sizes corresponding to $W \in \{3, 5, 7, 9\}$. Finally, we choose the estimate which maximises the a-posteriori probability (MAP).

$$\hat{\sigma}^2(i,j)=\max\left(0,\frac{1}{W^2}\sum_{(i,j)\in N} c^2\left(i,j\right)-\sigma_0^2\right),\quad (i,j)\in J \tag{1}$$

Where, $c(i, j)$ is the high-frequency component and $c \in \{H, V, D\}$; σ_0 controls the degree of noise suppression.

The minimum of four variances is chosen as the best estimate:

$$\hat{\sigma}^2(i,j)=\min\left(\sigma_3^2(i,j),\sigma_5^2(i,j),\sigma_7^2(i,j),\sigma_9^2(i,j)\right),\quad (i,j)\in J \tag{2}$$

An alternative, and less accurate method, is to simply use $W = 3$ as the estimated local variance.

The denoised wavelet coefficients are defined by the Wiener filter as follows:

$$c_{clean}\left(i,j\right) = \quad c(i,j)\frac{\hat{\sigma}^2\left(i,j\right)}{\hat{\sigma}^2\left(i,j\right)+\sigma_0^2} \tag{3}$$

Finally, the noise residual is obtained by calculating the inverse transform and subtracting the denoised image from the original image. JPEG and demosaicing artefacts, present in the noise image, are suppressed by subtracting the mean column and row values [7]. Greater weight is given to the green channel since due to the configuration of the color matrix this channel contains more information about the image [5, 17, 1].

The next step is to obtain features that characterise the sensor fingerprint for the purpose of classification. A total of 81 features (3 channels$\times$3 wavelet components$\times$9 central moments) is extracted using the Algorithm 2 as follows:

Algorithm 2: Extracting features

Input: Sensor fingerprint I_{noise}

Result: 81 features

procedure EXTRACTFEATURES(I)

Separate R, G and B color channels of I_{noise};

foreach *color channel* **do**

Apply a wavelet decomposition in 1 level;

foreach *component* $c \in \{H, V, D\}$ **do**

Compute k central moments with $m_k = \frac{1}{n}\sum_{i=1}^{n} |c_i - \overline{c}|^k$;

end procedure

Classification was performed using a SVM of the RBF kernel. We used the LibSVM package in which the SVM is extended to multiple classes yielding class probability estimates [6]. The kernel parameter $\gamma = 2^3$ and cost parameter $C = 32768$ were used for the SVM. We used a grid search in order to obtain the best kernel parameters (γ and C). The classifier was trained and tested with feature vectors extracted from randomly selected images.

4 Experiments and Results

To assess the effectiveness of the proposed algorithms, two experiments were conducted considering the central 1024x1024 pixel image block, as is widely recommended in [13]. Table 1 summarises the experimental conditions used in our algorithms.

Table 1. Parameters used in the proposed algorithms

Parameter	Value
Dimensions	1024 x1024
Number of training photos by camera	100
Number of testing photos by camera	100
Variance estimation	Non-adaptive

The mobile device digital cameras used and their configurations are showed in Table 2.

Table 2. Configurations used in mobile device digital cameras

Brand	Model	Resolution	Taking Conditions
Apple	iPhone3G (A1)	2 MP (1600x1200)	Scene type: Any Orientation: Vertical Flash: Disabled Light: Natural White balance: Auto Digital zoom ratio: 0 Exposure time: 0 seg ISO speed: Automatic
	iPhone4S (A2)	8 MP (3264x2448)	
	iPhone3 (A3)	2 MP (1600x1200)	
	iPhone5 (A4)	8 MP (3264x2448)	
Black Berry	8520 (B1)	2 MP (1600x1200)	
Sony Ericsson	UST25a (SE1)	5 MP (2592x1944)	
	U5I (SE2)	8 MP (3264x2448)	
Samsung	GT-I9100 (S1)	8 MP (3264x2448)	
	GT-S5830 (S2)	5 MP (2592x1944)	
	GT-S5830M (S2)	5 MP (2592x1944)	
LG	E400 (L1)	3.2 MP (2048x1536)	
HTC	DesireHD (H1)	8 MP (3264x2448)	
Nokia	E61I (N1)	2 MP (1600x1200)	

4.1 Experiment 1

In this experiment, a group of 8 mobile device digital cameras from 4 different manufacturers was tested. From Apple, the models iPhone3G (A1), iPhone4S (A2), and iPhone3 (A3) were considered; from BlackBerry the 8520 (B1); from Sony Ericsson the UST25a (SE1) and the U5I (SE2); and from Samsung the GTI9100 (S1) and the GTS5830 (S2) models.

The performance of the classifier was tested 10 times, using a 10 different random samples of 100 images, and the average classification rate recorded. The performance changed only slightly in each run which indicates stability over different training and testing image sets.

The PRNU extraction algorithm and feature extraction algorithm are implemented in Python 2.7 with an Intel Core i5, 2.5-GHz processor and 8 GB of RAM. It takes approximately 40s to extract the PRNU and compute the features for a single image. Training the SVM classifier and testing is realized in a 2s and fraction of a second respectively. A random sample of 100 images was used for testing a different random sample of 100 images was used for testing.

Sample confusion tables from eight camera groups are given below. The best, middle, worst case tables are show in Tables 3, 4 and 5 respectively. The average accuracy for correctly identifying camera make and model was 93.2%.

Table 3. Confusion matrix of best result (93.87%)

Camera	A1	A2	A3	B1	SE1	SE2	S1	S2
A1	**96**	1	0	0	0	0	0	3
A2	0	**97**	0	0	0	0	3	0
A3	0	0	**98**	0	0	0	2	0
B1	0	0	0	**94**	0	4	0	2
SE1	11	1	0	0	**88**	0	0	0
SE2	3	0	0	1	0	**93**	1	2
S1	4	8	0	0	0	3	**85**	0
S2	0	0	0	0	0	0	0	**100**

Table 4. Confusion matrix of middle result (93.25%)

Camera	A1	A2	A3	B1	SE1	SE2	S1	S2
A1	**94**	1	0	0	0	1	0	4
A2	0	**96**	0	0	1	0	3	0
A3	0	0	**97**	0	0	0	2	1
B1	0	0	0	**94**	0	2	0	4
SE1	10	1	0	0	**89**	0	0	0
SE2	2	0	0	1	0	**94**	1	2
S1	5	6	0	0	0	6	**83**	0
S2	0	0	0	0	0	1	0	**99**

Table 5. Confusion matrix of worst result (92.62%)

Camera	A1	A2	A3	B1	SE1	SE2	S1	S2
A1	**92**	1	0	0	0	0	0	7
A2	0	**96**	0	0	1	0	3	0
A3	0	1	**99**	0	0	0	0	0
B1	0	0	3	**91**	0	4	0	2
SE1	7	2	0	0	**91**	0	0	0
SE2	2	0	0	1	0	**94**	1	2
S1	4	10	0	0	0	7	**79**	0
S2	0	0	0	0	0	1	0	**99**

4.2 Experiment 2

In order to evaluate the scalability of the method to a larger number of classes, a group of 14 mobile device digital cameras from 7 different manufacturers was used.

Table 6. Confusion matrix of experiment 2

Camera	A1	A2	A3	A4	B1	SE1	SE1	S1	S1	S3	L1	H1	H2	N1
A1	**90**	0	0	2	0	0	0	0	7	0	1	0	0	0
A2	0	**91**	0	3	0	0	0	3	0	0	0	1	2	0
A3	0	0	**98**	0	0	0	0	2	0	0	0	0	0	0
A4	0	0	1	**88**	0	0	0	0	0	0	3	6	0	2
B1	0	0	0	2	**73**	0	0	0	4	0	0	1	0	20
SE1	7	0	0	0	0	**80**	0	0	0	0	1	12	0	0
SE2	1	0	0	2	2	0	**86**	1	2	5	1	0	0	0
S1	4	5	0	4	0	0	1	**83**	0	0	1	0	2	0
S2	0	0	0	0	0	0	0	0	**100**	0	0	0	0	0
S3	0	0	1	0	0	0	8	0	0	**85**	0	1	0	5
L1	0	0	0	9	0	6	0	0	2	0	**70**	13	0	0
H1	2	0	0	0	0	11	0	0	1	0	1	**85**	0	0
H2	0	6	0	0	0	0	0	0	0	0	0	0	**94**	0
N1	0	0	0	0	2	0	0	0	0	0	0	0	0	**98**

From Apple the models iPhone3G (A1), iPhone4S (A2), iPhone3 (A3) and iPhone5 (A4) were considered; from BlackBerry the 8520 (B1); from Sony Ericsson the UST25a (SE1) and the U5I (SE2); from Samsung the GTI9100 (S1), the GTS5830 (S2) and the GT-S5830M (S3); from Lg the E400 (L1); from HTC the DesireHD (H1) and the Desire (H2); finally from Nokia the E61I (N1) model.

The average classification rate dropped to 87.214% as shown in the confusion matrix of Table 6 indicating a small loss in performance when the number of classes (cameras) is increased.

5 Conclusion

According to the structure and operation of mobile device digital cameras the most appropriate techniques for forensic analysis are the those based on sensor noise and wavelet transforms. In the foregoing it was proposed an algorithm for identifying the mobile source combining techniques based on sensor fingerprint and the wavelet transforms. The algorithm is mainly composed of two phases, the first is dedicated to extract the sensor fingerprint, and the second to extract features from this fingerprint which will serve as input to the SVM used as classification method.

The effectiveness of a method for source camera identification, based wavelet features of image noise residuals, was tested on photographs acquired from a range of smartphones. In the first experiment 8 models from 4 manufacturers were considered resulting in an overall accuracy of 93.2%. In order to evaluate the scalability of the approach, we repeated the experiment using 14 models from 7 manufactures and achieved an average success rate of 87.214%. Our results, tentatively, suggest that the method is applicable to data sets containing images from a large number of different cameras and therefore the method promises potential utility for digital forensics and data mining applications.

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